Project ID# : EEMS077
Pillar: Mortar

U.S. DEPARTMENT OF ENERGY
SMARTMOBILITY
Systems and Modeling for Accelerated Research in Transportation

Transportation System Control for Taxi/Transportation Network Company Simulations

Joshua Auld
Felipe De Souza
Argonne National Laboratory
2019 Vehicle Technologies Office Annual Merit Review
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Argonne NATIONAL LABORATORY
INL Idaho National Laboratory
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Project Overview

SMART MORTAR Task: Transportation System Control for Taxi/Transportation Network Company Simulations

Timeline	Barriers
• Project start date : 10/1/2018 • Project End date : 9/30/2019 • Percent complete : 40%	• High uncertainty in technology deployment, functionality, usage, impact at system level • Computational models, design and simulation methodologies • Lack of data on individual behaviors relating to CAV adoption and usage • Integration of disparate model frameworks
Budget	**Partners**
• FY19 Funding Received : $375,000	• Argonne (Lead) • University of Texas – Austin • University of California – Irvine • University of Washington • LBNL

Project Relevance

- Implementing TNC fleet and vehicle agents
- Mode choice updated under EEMS078 to reflect TNC use

FY19Q2

- TNC vehicle reposition optimization
- Dynamic ride-share assignment
- TNC driver behavior models

FY19Q3

- Calibration and validation of TNC model against CMAP data
- Case studies of TNC/taxi in Chicago

FY19Q4

Challenges:

- TNC usage in cities is growing steadily and becoming significant portion of travel
- Models and data on TNC operations, however, are limited
- TNC is likely to be an increasingly important component of SMART mobility solutions
- High degree of interconnection between decision-making, transportation system performance and development of Smart Mobility technologies related to TNC

Objectives and Relevance:

- Consider the **behaviors of individual** travelers, drivers and fleet operators jointly
- Assess influence of TNC operational characteristics on **mobility energy productivity**
- Understand **TNC vehicle operational characteristics** and impact on VTO vehicle technology portfolio

Milestones

QPM: Taxi/TNC fleet manager implemented in POLARIS

19Q1 | 19Q2 | 19Q3 | 19Q4

Annual: Case study simulation of Chicago taxi and TNC fleets

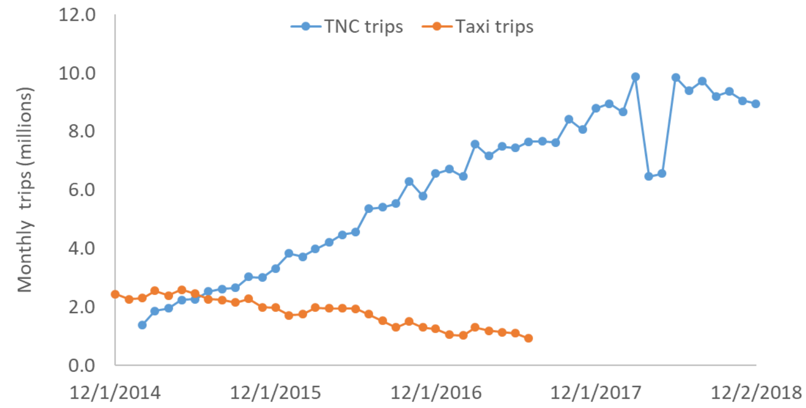
- Task completed
- In progress
- On track

APPROACH

TAXI AND TNC DATA SOURCES ON OPERATIONS & BEHAVIOR

Chicago taxi and TNC trip data

- Taxi data previously available, TNC data released in April 2019
  - Preliminary data exploration started
  - 4.8 million monthly driver records 17.4 million trips since 12/2014
- TNC increase by 548% while taxi declined by 62% since 12/14
- Approximately 10 TNC trips per taxi trip in 2018



UW survey

If you had to make a **15-mile commute trip**, which of the following options would you choose?

Personal Car	Ride-hailing Service
Travel Time: 20 min	Travel Time: 15 min
Travel Cost: $5 (fuel, tolls, parking, etc.)	Travel Cost: $15 (fare)
Waiting Time: 0 min	Waiting Time: 2 min
Activity: Driving	Activity: Non-Driving(e.g. work, read, rest, using cellphone..)

- ○ Personal Car
- ○ Ride-hailing Service

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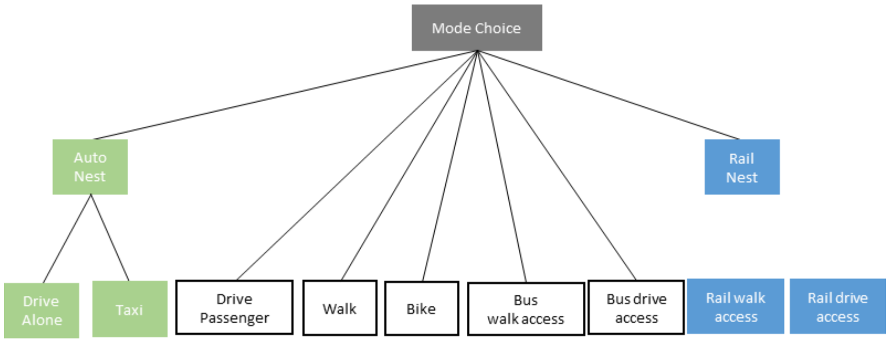
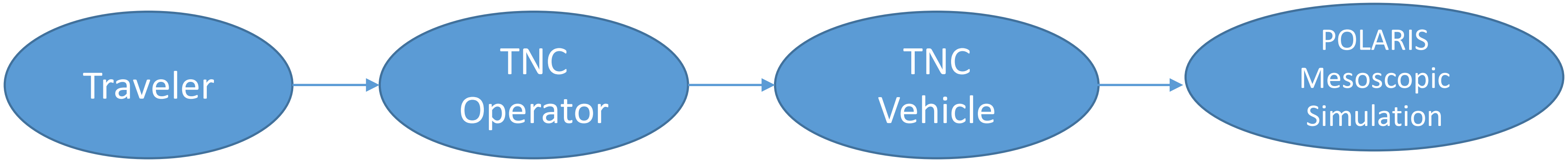
FTA Survey + CMAP mode choice model



TNC SIMULATION ELEMENTS



- Request trips when convenient (behavioral model)
- Cancels the trip if pick-up time exceeds a timeout

- Travelers request a ride through a specific operator which then assign to specific vehicle
- Multiple operators can coexist on the same scenario
- Repositioning strategy

- Inherits all features of POLARIS vehicles (charging for EV's, Routing, etc)
- Schedules pick-up and drop-offs according to operator requests
- vehicle-specific seated capacity

- Experienced travel times
- Account for automation level when TNC vehicle is a AV

- Vehicle modelling
  - Inherits all features of POLARIS vehicles (charging for EV's, Routing, etc)
  - Schedules pick-up and drop-offs according to operator requests
  - vehicle-specific seated capacity
- Operator Modeling
  - Travelers request a ride through a specific operator which then assign to specific vehicle
  - Multiple operators can coexist on the same scenario
  - Repositioning strategy
- Traveler Modeling
  - Requests the trips when convenient
  - Cancels the trip after a timeout

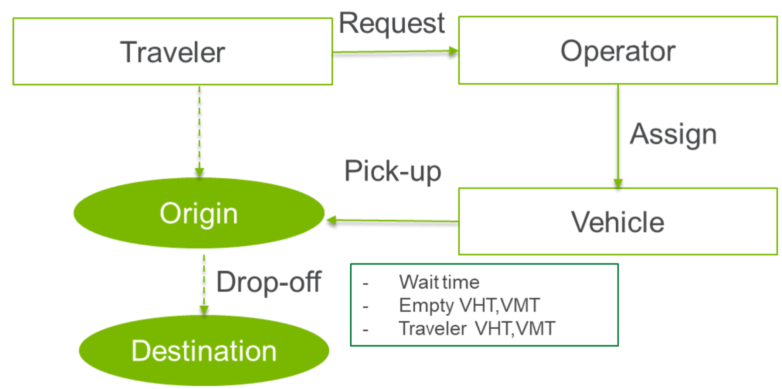
SAV FLEET OPERATOR AND CONTROL ALGORITHMS DEVELOPED IN POLARIS – ADAPTED TO TNC FLEETS

- Key tasks:
  - Develop SAV operator and SAV vehicle agent code and algorithms
  - Integrate SAVs with advanced operational strategies into POLARIS
  - Policy impact analysis (of better real-time ride-sharing, restricting SAV operation & station aggregation)
- Key features:
  - Handle large number of ride requests:
    - 350,000 vehicles in Scenario A
  - Spatial-indexing for closest matching rider to vehicle
  - Repositioning algorithms (currently based on zone-level wait times
- Currently developing:
  - Optimization-based repositioning scheme
  - Dynamic ride-sharing optimizer

Customizable operator model in POLARIS


```
"SAV_Fleet_Model": {
  "NO_OF_OPERATORS": 1,
  "OP_1": "Operator_1",
  "SAV_DISCOUNT":  0.5
},
"Operator_1": {
  "Operator_1_SAV_FLEET_SIZE": 35000,
  "Operator_1_SAV_MAX_WAIT_TIME": 20,
  "Operator_1_SAV_MAX_SEATED_CAPACITY": 4,
  "Operator_1_SAV_MAX_SEARCH_RADIUS": 10.4,
  "Operator_1_SAV_LOGGING_INTERVAL": 120,
  "Operator_1_geofence_flag": false,
  "Operator_1_geofence_areatype_limit": 2
}
```


Traveler SAV request process



TNC DRIVER BEHAVIOR MODELING

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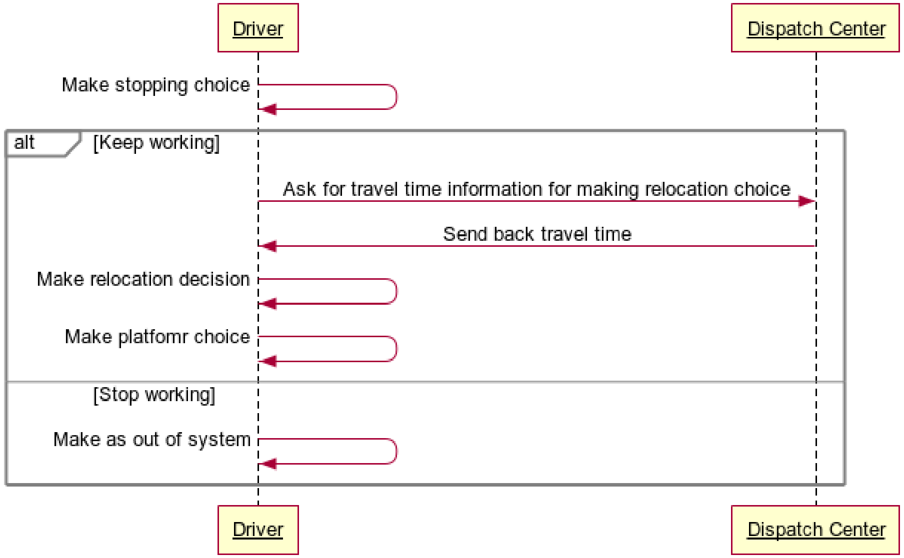
- Model framework developed:
  - Currently collecting data to estimate model components
  - Exploring use of Chicago TNC data to estimate model components
- TNC drivers engage in multiple decision types that influence availability of vehicles to service pickups including:
  - Platform choice
    - Uber v. Lyft v. other
  - Relocation decision:
    - Find more profitable place to wait
    - Guided by platform or user knowledge
  - Respond to a request: accept or not
  - Stop shift
- Will be implemented as variety of choice models as shown

Source: Sijie Chen, University of Washington

Different models for different driver choices:

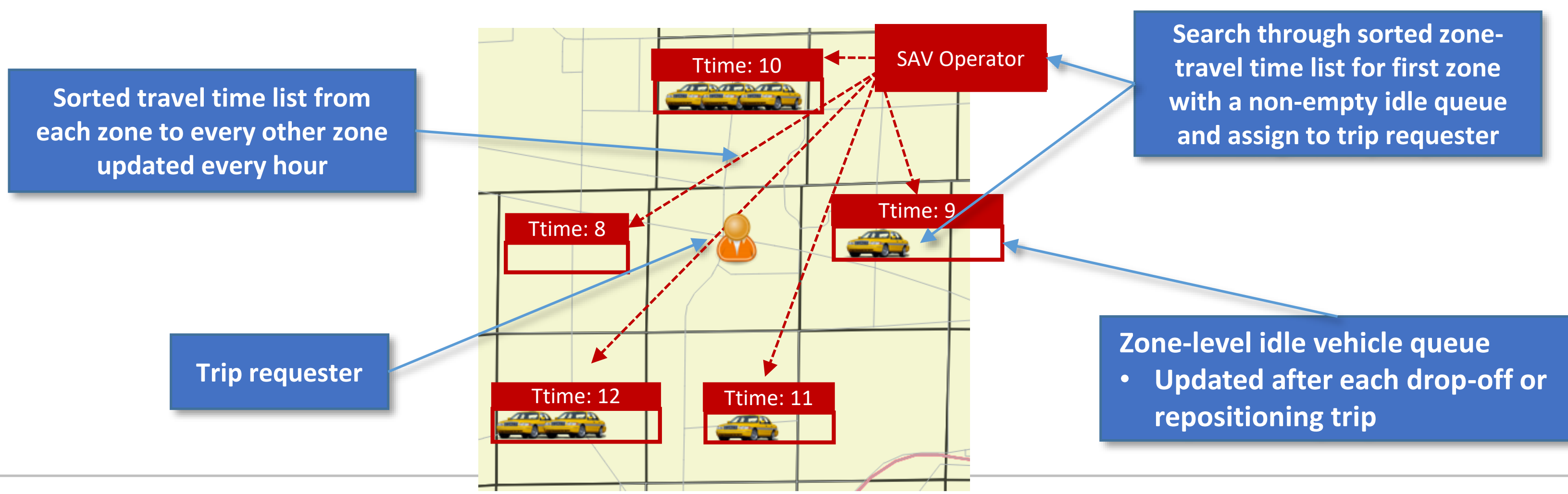
Platform choice	Markov Decision Process, reinforcement learning algorithm
Relocation choice	Nested logit model
Response to a request	Binary logit model
Decision to stop	Survival time model

Process diagram for driver behavior:



OPERATOR ASSIGNMENT

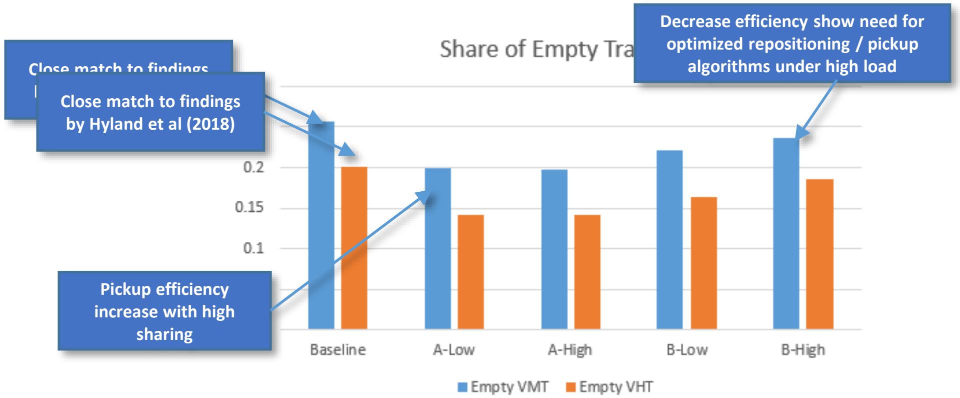
- Ride-Matching: Computationally efficient structure to support millions of trips
  - Assign a vehicle from the closest zone that has an idle taxi within search range
  - A vehicle is in the search range if is within 15 minutes predicted travel time
  - Periodically attempts if a vehicle is not available within the range
  - Computationally efficient structure to support millions of trips
- Support for Multiple TNC/TAXI fleet operators (e.g., Uber, Lyft, others)
- Exploring external optimization models for trip assignment



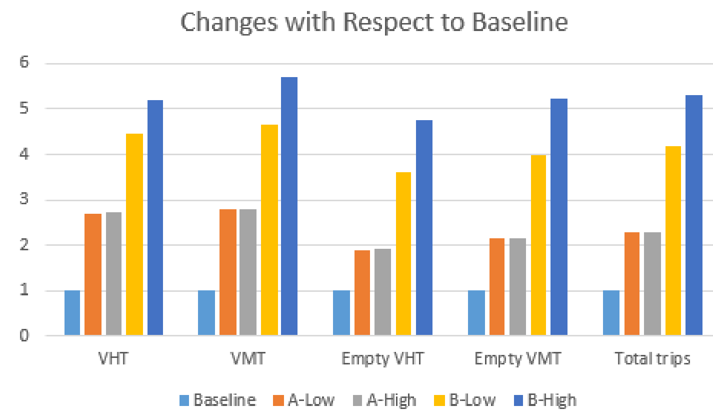
TECHNICAL ACCOMPLISHMENTS AND PROGRESS

TNC/SAV USE INCREASES SUBSTANTIALLY FOR THE SHARED AND HIGH TECH SCENARIOS

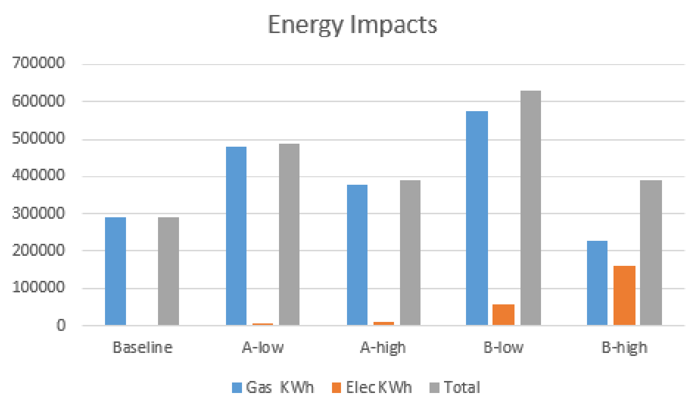
Pickup / repositioning are large fraction of total TNC miles



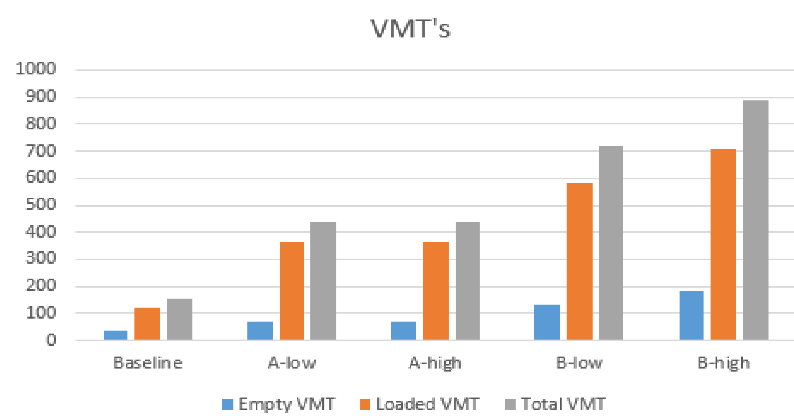
Total pick-up/repositioning and drop-off operations



Energy use impacts of SAV



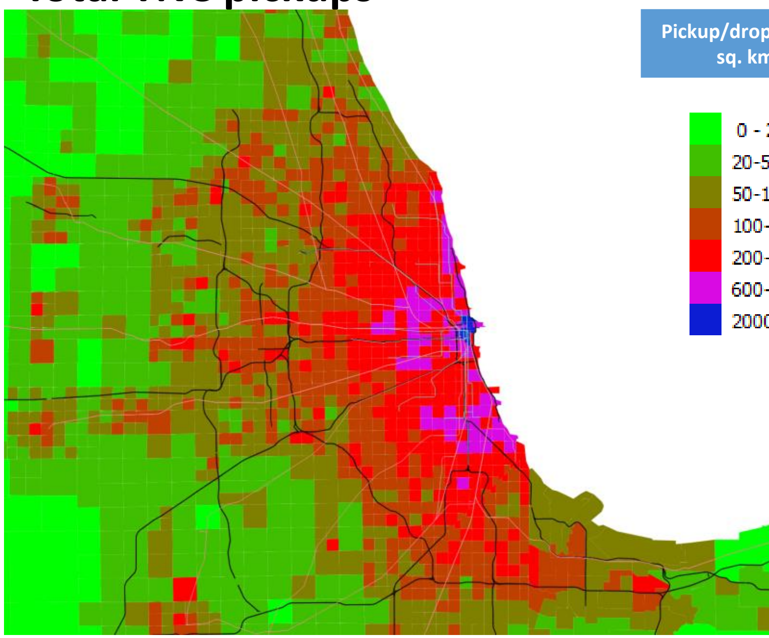
Total auto VMT (private and shared) by scenario



TNC GIS DISTRIBUTION

Pickup & Dropoffs concentrated downtown but still many occur in the suburbs

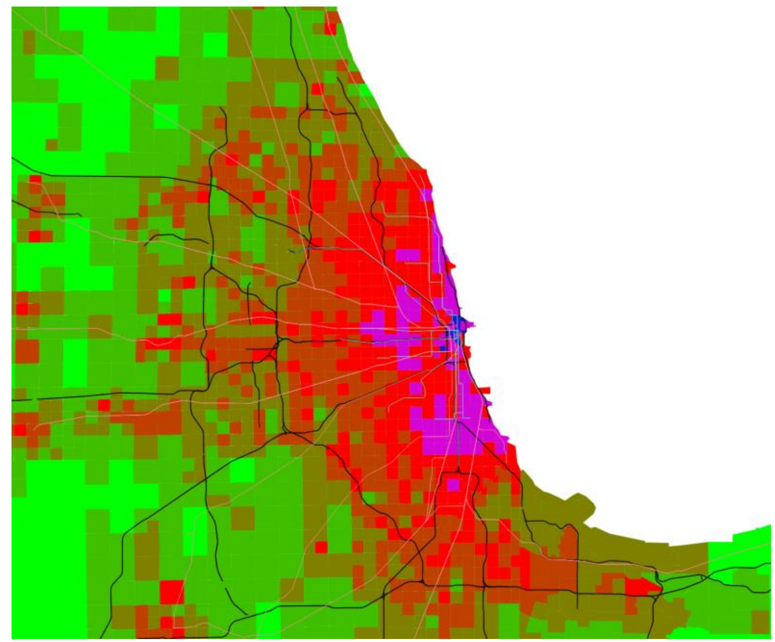
Total TNC pickups



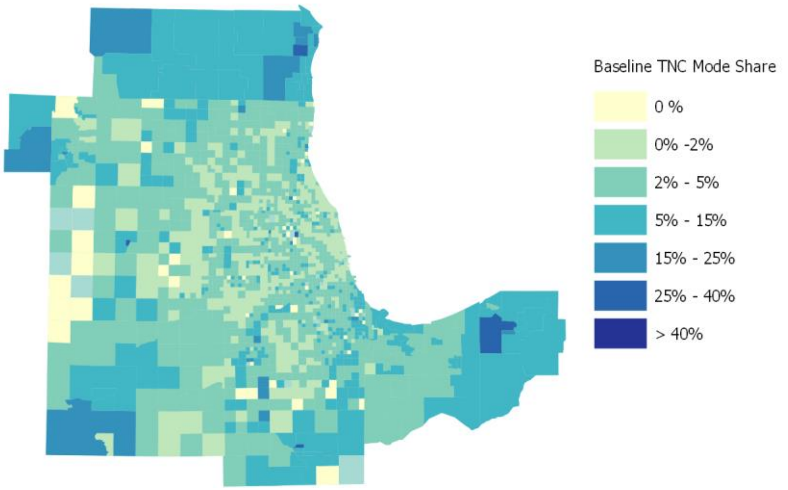
Pickup/dropoff per sq. km

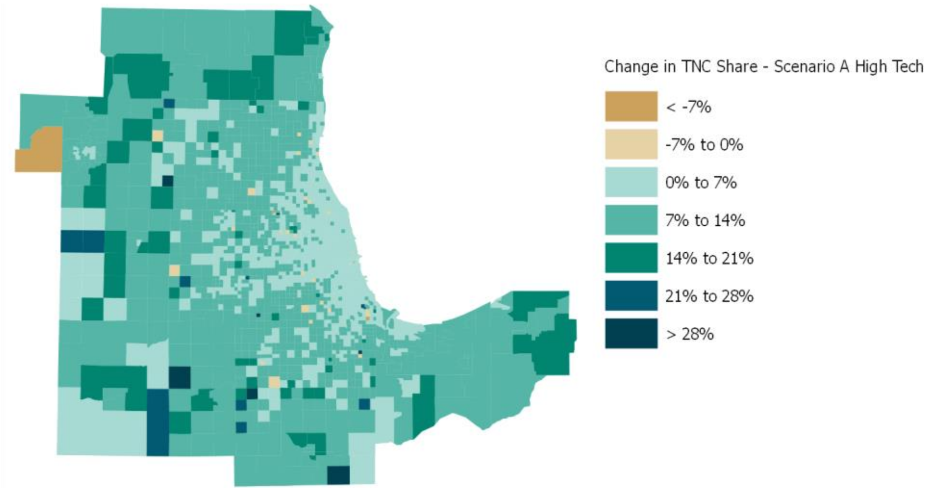
- 0 - 20
- 20-50
- 50-100
- 100-200
- 200- 600
- 600-2000
- 2000+

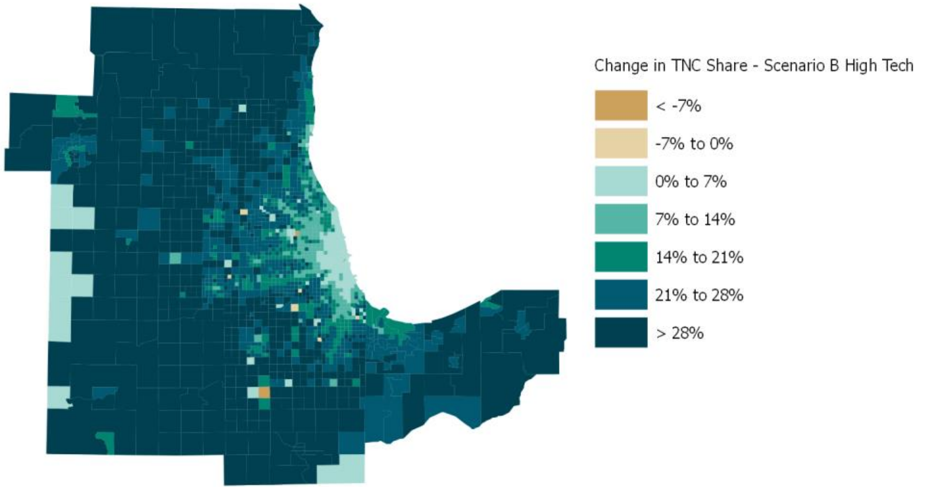
Total TNC dropoffs



TNC MODE SHARE – BASELINE AND %CHANGE

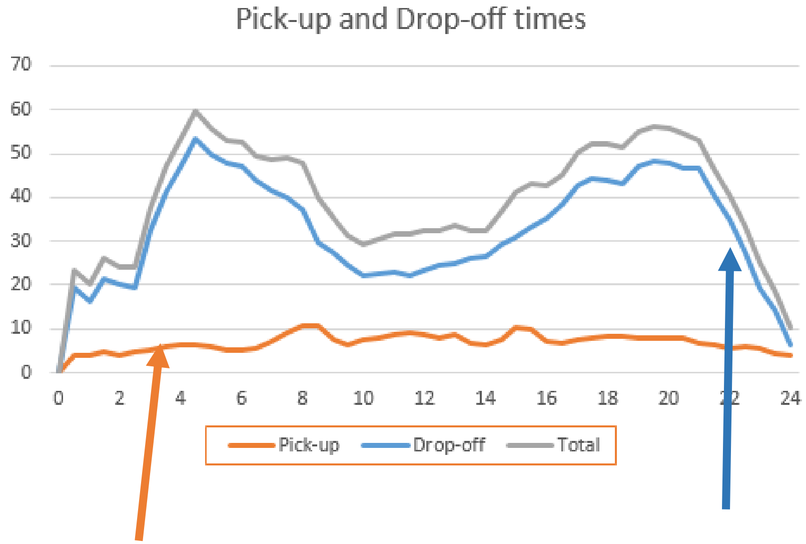






TNC RESULTS

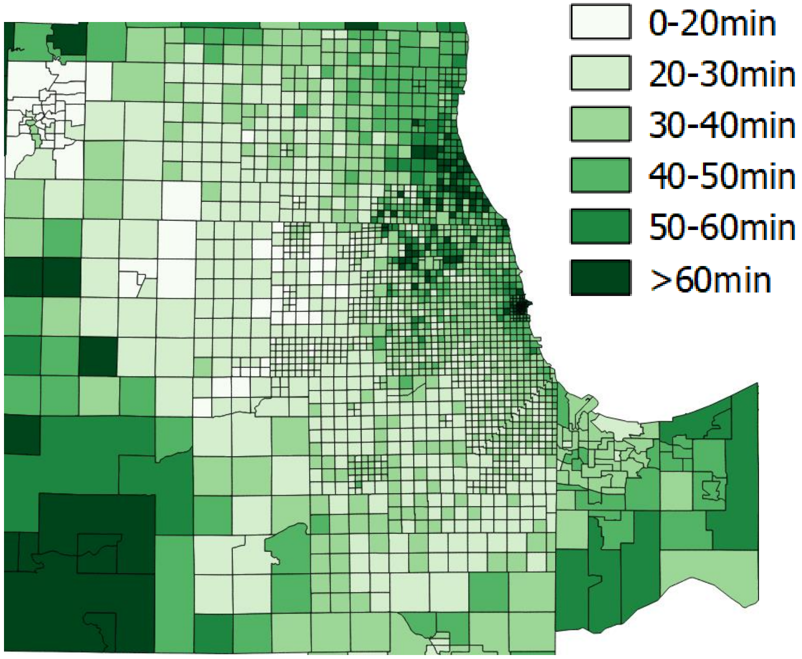
- Temporal VHT Distribution



Time spent looking for / going to customers

Time spent driving customers to their destination

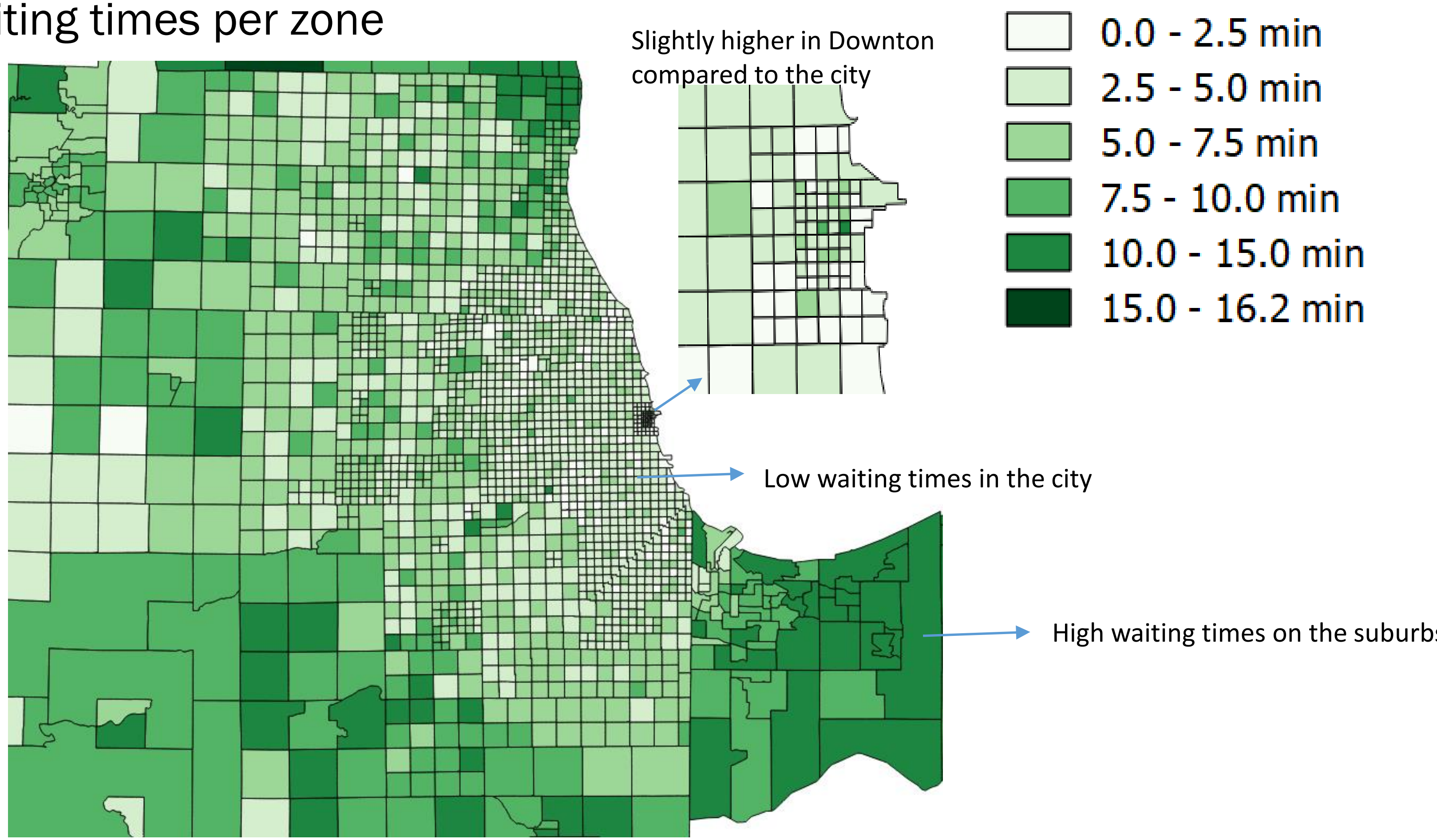
- Spatial Distribution of travel times



High in downtown and suburbs

WAITING TIMES PER ZONE

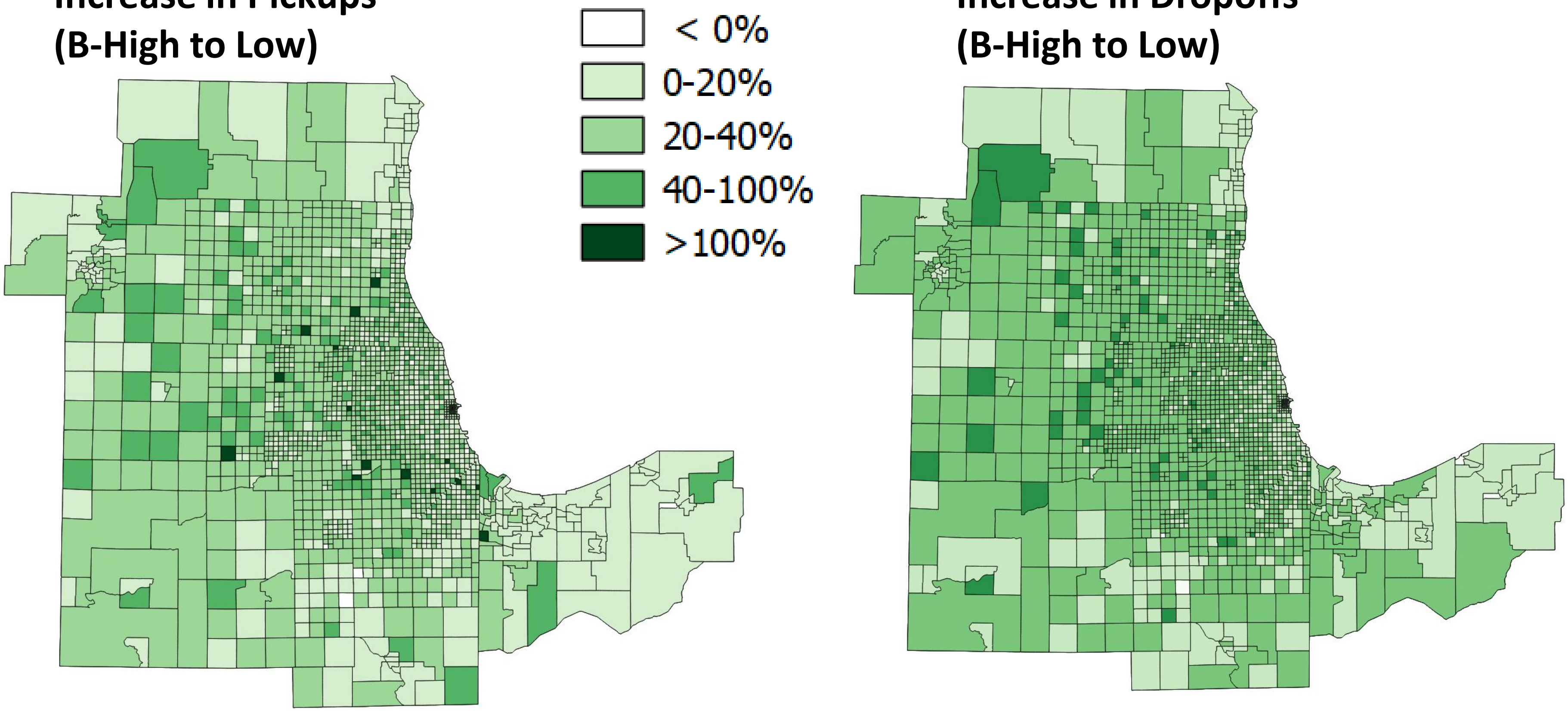
- Waiting times per zone



IMPACT OF AUTOMATION LEVEL (SCENARIO B)

Increase in Pickups (B-High to Low)

Increase in Dropoffs (B-High to Low)



RESPONSES TO PREVIOUS YEARS REVIEWERS COMMENTS

- This project was not reviewed last year

COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS

U.S. DEPARTMENT OF ENERGY SMARTMOBILITY Systems and Modeling for Accelerated Research in Transportation	EEMS017, EEMS075, EEMS078
UCIrvine	TNC repositioning optimization
The University of Texas at Austin	Dynamic rideshare modeling
W UNIVERSITY of WASHINGTON	TNC driver behavior and travel survey
BERKELEY LAB	TNC pickup/drop off impact on traffic flow
CDOT CHICAGO DEPARTMENT OF TRANSPORTATION	Local modeling and analysis stakeholders; data providers

REMAINING CHALLENGES AND BARRIERS

- TNC operational modeling:
  - Number of vehicles operating change throughout the day (more vehicles on the peak): constant fleet size may underestimate off-peak waiting times
  - Investigate different assignment policies and relocation strategies
  - Analyze the effect of spatially constrained SAV"s ("geofencing")
  - Understand trade-off between operating cost, pricing, waiting times and operational relocation strategies
  - Dynamic ridesharing can reduce empty miles: how to implement efficiently
- Data Limitations:
  - No data on fleet operation and assignment: trade secrets for TNCs
  - Traveler behavior regarding price change and ride share: TNC mode only now starting to show up in regional household travel surveys in large numbers

PROPOSED FUTURE RESEARCH

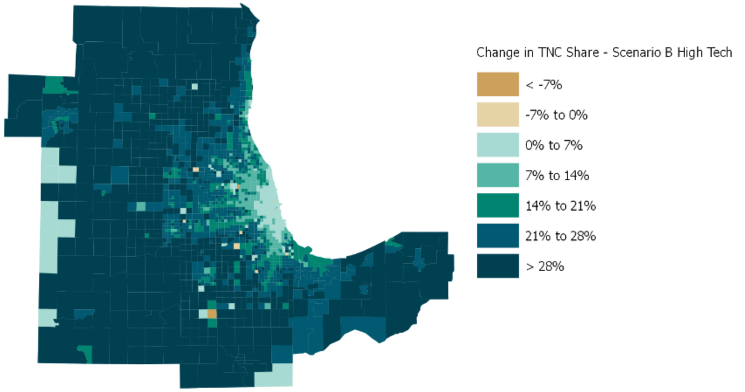
- Explore optimal assignment strategies:
  - Incorporating dynamic ride-sharing
  - Consider charging events or battery exchange in the operation
  - Station-based operation
  - Restriction for pick-up in specific geographic areas ("geofencing")
- Opportunities for transit integration:
  - Investigate different schemes with TNC as a feeder to transit stations
  - Prices based on transit accessibility
  - Initial SMART mobility scenario exploration shows feasibility of this
- Include traffic impacts of TNC through simulation:
  - TNC, SAV, delivery impacts of traffic flow through pickup/drop-off/stop
- Different assignment models for new business cases:
  - Fleet operation with trips scheduled in advance (e.g. for disabled population)
- Integration with System-Level Optimization
  - Incentivize routes or departure-time changes

Any proposed future work is subject to change based on funding levels

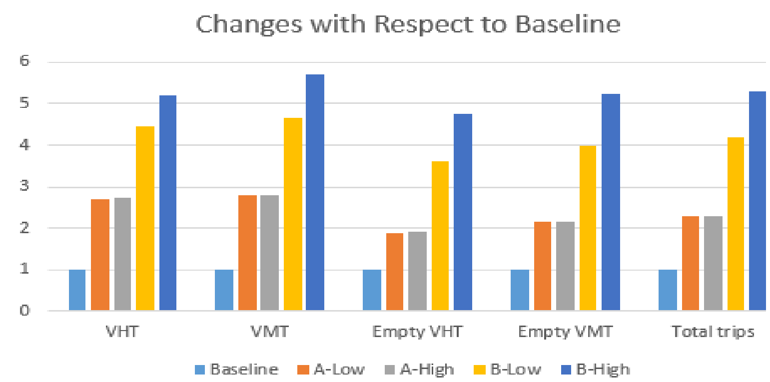
SUMMARY

- Developed detailed workflow that combines:
  - regional mobility
  - land use
  - traffic microsimulation
  - Vehicle simulation
  - Fleet optimization, etc.
- Deployed as part of SMAR workflow to examine multiple scenarios:
  - shared vehicle use,
  - increased vehicle technology
  - changes in travel and shopping behavior
- **Key findings:**
  - ↑ shared use ↑ mobility energy productivity
  - High TNC use and transit can be complementary
  - TNC share likely to increase in suburbs

Map comparing B-high to Baseline



Key travel metrics by scenario



QUESTIONS?